

The One Percent Per Week TQQQ Trading Strategy:

MAKING IMPROVEMENTS

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In this article, my interest will be in finding ways to improve the overall long-term performance of this outstanding trading strategy.

I cannot predict the price move for next week. However, over a long trading interval, I can make averages of what I consider as the average behavior for the trades taken and determine if those averages can persist. It will make a difference in how we view our long-term goals.

We might not know the outcome of a coming short-term trade, as if its result were subject to a coin flip. But we still know that, on average, our trading strategy does so and so. Its past behavior is already telling us something that might be more valuable than we think.

In my latest paper published March 20, 2025: [The One Percent Per Week TQQQ Trading Strategy: MY EQUATION](#), I explored the use of my portfolio equation to describe the inner workings and foundation of the **One Percent Per Week** (OPPW) strategy trading the 3x-leveraged TQQQ ETF, elaborated on its properties and potential forecasting abilities.

We should not be surprised by the showcased results in this article since we will be dealing with a 3x-leveraged ETF (TQQQ). If QQQ (which TQQQ is tracking) can generate about 15-17%+ long-term,¹ then we should expect a ballpark figure of 45-51%+ for TQQQ's long-term compounded annual growth rate (CAGR).

TQQQ recently celebrated its 15th anniversary. Since its inception, it has had the highest CAGR in the ETF space (40%+).²

The TQQQ trading strategy will be compounding for 15+ years in these simulations, having quite a performance difference overall. Compare a 10% to a 50% CAGR: we have $(1 + 0.10)^{15} = 4.177$ and $(1 + 0.50)^{15} = 437.894$ which should generate 100 times more. Putting these in numbers we have:

$\$100,000 \cdot (1 + 0.10)^{15} = \$417,724$ compared to $\$100,000 \cdot (1 + 0.50)^{15} = \$43,789,389$

Yet, we can easily do better than that.

¹ See my articles on QQQ in the related articles.

² Refer to the [TQQQ](#) website page.

It is not the short-term CAGR we should be interested in; it is the long-term CAGR, which can persist for years and years.³ Or at least, as in this case, gradually get there and achieve those higher CAGR after years of trading.

Trading TQQQ also means market swings with higher amplitude. The ride will be more bumpy but not worthless. Higher returns should be easy to reach if, from the start, you deal with something that fluctuates 3x more than the traditional market averages. You should expect 3x the average market return.

One serious advantage of using TQQQ is that it is 3x-leveraged, but you have no leveraging fees, only management fees (less than 1% per year). Since the strategy is in the market only 52% of the time or about, even those fees will be near half the yearly expense.

THE QUEST FOR IMPROVEMENTS

It is time to consider: *How and where to improve on this trading strategy?* Especially since we have an equation that can determine its long-term outcome.⁴

I will use some of the material presented in the above-cited paper that I will also reference as the *GRF Equation*. There is no need to redo some of the simulations.

From the OPPW, we got an equation that explained the strategy's outcome. And from it, we could make estimates on what it might do in the future on the same basis we analyzed its past. The OPPW strategy will most likely do nearly the same things in the future as it did in the past.

The requested precondition is to have a number of trades large enough so that the average portfolio metrics could be viewed as having reached the status of long-term averages.

Here is my equation again:

$$F(t) = \bar{e} \cdot f_0 \cdot \prod_1^N (1 \pm r_i) = \bar{e} \cdot f_0 \cdot (1 + \bar{r}_+)^{N-\lambda} \cdot (1 - \bar{r}_-)^{\lambda} \quad (1)$$

What is outstanding in the *GRF Equation (1)* is that using portfolio simulation metrics, we can assess the total outcome of the trading strategy over the N executed trades.

Due to its generic nature, we could also use the equation in other trading strategies.

³ As Einstein once said: "compounding is the 8th wonder of the world."

⁴ Refer to the above-cited paper, which has many simulations spanning up to 20 years. The saying: "If it ain't broke, don't fix it" will not apply here. We are looking to make the strategy better.

Table #1: List Of Variables

Variable	Description	Origin Of Value
\bar{e}	average exposure rate	from simulation result
f_0	initial trading capital	your initial capital
γ	leveraging factor	calculated after sim
N	number of trades	from simulation result
λ	number of losing trades	from simulation result
$N - \lambda$	number of winning trades	from simulation result
ν	number of added trades after reaching N	for forward estimates
\bar{g}	portfolio's growth rate	from simulation result
$\pm r_i$	return for trade i	from simulation result
\bar{r}_+	average percent win on winning trades	from simulation result
\bar{r}_-	average percent loss on losing trades	from simulation result
t	long-term trading interval	you determine

Table #1 gives the same variables list as in the above-cited paper. I will also use them in this article. The list provides the origin of those variables and where you can find them; most come from WL8 simulation metrics.

My interest will be mosly on N , λ , ν , \bar{r}_+ , \bar{r}_- , and \bar{g} . These can have quite an impact on equation (1).⁵

I want to determine the past performance of this trading strategy using equation (1) and use it to predict its future, at least get a range for these expected long-term average returns.

On top of that, I want the equation to show where we can make improvements and what we should expect from those program modifications even before we make them. Stating: make this or that improvement, and it will generate such and such.

We can design quasi-randomly generated trading scenarios using equation (1). If we run enough of these random-walk scenarios, we could use their long-term averages as expected outcomes within an acceptable range. We are not looking for exact numbers but expect those ballpark figures to be reasonable estimates.

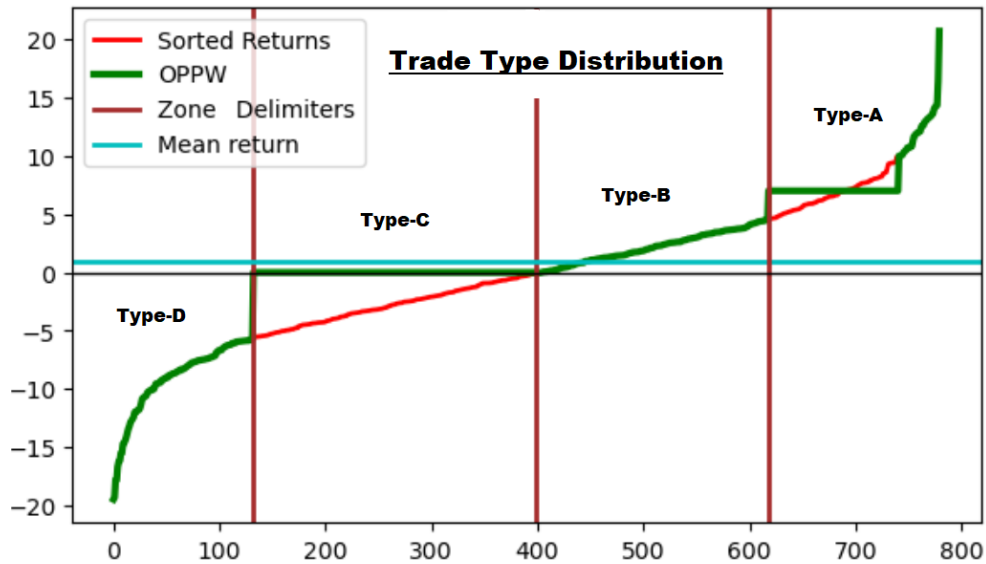
An important chart from the above-cited free paper is the trade type distribution (Figure #1 below).

From the trading rules of the strategy, the generated outcomes were sorted by return and ranked in those trade types.

The numbers came from the WL8 program simulation's result, and the trade types depended entirely on the trading rules adopted.

⁵ Note that the time you stay invested (t) gets to be critical.

Figure #1: Trade Type Distribution.



[\(Click here to enlarge\)](#)

These trading rules were really simple.⁶

The future remains uncertain, but it tends to average out over the long haul.

I will again do simulations to demonstrate the impact of the modifications applied to the trading procedures, knowing the equation's outcome depends on the changes to the trade distribution. Already, in my *GRF Equation*, I presented many scenarios.

Figure #1 presents the four trade types for this strategy, and all four are relevant. When taking a trade, you do not know which of the four trade types it will fall into. But you know it will end up in one due to the one-week time limit on these trades.

Our advantage is we have 780 trades ($N = 780$ weeks) taken over the 15 years of TQQQ price data. From there, we can take the average outcome for each type of trade. The Wealth-Lab 8 (WL8) simulation⁷ showed that the portfolio metrics answered to equation (1) as was also provided in the Python code of Figure #4 from the same paper.

Using the WL8 simulation's portfolio metrics, and applying them to equation (1), we would have the following:

$$F(t) = 0.52 \cdot \$100,000 \cdot (1 + 0.0452)^{405} \cdot (1 - 0.0272)^{379} = \$89,678,997 \quad (2)$$

which is relatively close to the simulation's results. The difference from the simulation outcome is due to the rounding of the average percent gain or loss, which is

⁶ See my article: [Your Trading Rules Matter](#).

⁷ See Figure #5 in [The One Percent Per Week TQQQ Trading Strategy: MY EQUATION](#).

compounding over a large number of trades. Even a small difference in the average percent win per winning trade will be raised to the 405th power.

One thing to note from equation (2) in those factors are after 784 trades (15+ years). We have enough trades for them to reach the status of long-term averages. All the simulations will tend gradually to those numbers after 15 years of trading. They all should converge to those numbers by year 15, coming from randomly generated paths.

These scenarios could result in large numbers since each trade is part of the compounding series. You have one percent per month, giving you a rate of 12.68%: $(1 + 0.01)^{12} = 1.1268$, something you could get by buying and holding SPY.

However, with the OPPW strategy, you opted to accelerate the process and go for, on average, a 1% return per week: $(1 + 0.01)^{52} = 1.6776$. A 67.76% gain. It has to be a game-changer. Especially if you can demonstrate that 1% return per week with a WL8 simulation giving those numbers and that you can verify on your own.

Moreover, you intend to do this not for one year but for 15+ years. You aim to reach something like $(1 + 0.01)^{52 \cdot 15} = 2347.8565$, multiplying your initial capital by 2,347 times over those 15 years. Compare that to holding SPY: $(1 + 0.01)^{12 \cdot 15} = 5.9958$, which would grow by 6 times over the same period.

From the WL8 simulation result, you can count the number of trades falling in each of the four types. Table #2 below gives that trade distribution breakdown taken from the February 8th simulation:

Table #2: WL8 Trade Statistics – February 8th, 2025

Trade Type	Trade Outcome	Trade Result	# Trades	≈ Percent Of Total	Reason Position Sold	Average # Trades/Year
A	Positive	≥ 7%	135	≈ 17.26%	Above Profit Target	9.0
B	Positive	> 0 < 7%	269	≈ 34.39%	On Friday's Close	17.9
C	Zero	= 0	222	≈ 28.38%	Break Even	14.8
D	Negative	< 0	156	≈ 19.94%	Losing Positions	10.4
Total →			782			

You had a 51.65% chance of generating a profit while 19.94% of those trades would be losing money. You also had a 28.38% probability of generating absolutely nothing at all (Type-C trades). We might have envisioned a 4-way split (25% or thereabout for each type) for a randomly distributed scenario, but the market does not behave that way. Nonetheless, the strategy's hit rate was close to a 50% split.

One thing that Table #2 does emphasize is that you will not win all the time. On average, one in five trades will generate a loss, about 10 per year. And some of those losses are inevitable. Therefore, added downside protection is highly recommended.

THE SIMULATIONS

I will go directly to Figure #10 (replicated below as Figure #2) from my *GRF Equation* paper, where several 10,000 simulations were performed over 15 years of TQQQ simulated data.

Figure #2 uses the Python code in Figure #4.⁸ An added `for loop` was used for the 10,000 iterations. I only listed every 500 simulations. It was sufficient to show the wide range of outcomes.

Figure #2 includes the number of trades associated with each type. We can compare the simulation results with the first line in the chart, where we have the distribution of the trade types according to the outcome of the WL8 simulation:

$$F(t) = 0.52 \cdot 10,0000 \cdot (1 + 0.082)^{135} \cdot (1 + 0.0301)^{269} \cdot (1 + 0.00)^{222} \cdot (1 - 0.0596)^{156} \quad (3)$$

Equation (3) derives from the WL8 simulation, where trades were counted and classified according to their respective trade types. For example, if a trade hit its profit target (8.2%), it increased the count by one. If you added more trades, they would all be at that profit target price since they are the outcome of those sell-limit orders waiting in the books.

From Figure #2, we can observe that the strategy's equation could be very sensitive to the distribution of the trade types.

Figure #2: 10,000 Simulations over the 15 years of simulated trade data.

WL8 Sim \$	86,642,514	Sim Feb. 21	(A: 135, B: 269, C: 222, D: 156)	CAGR: 56.86 %
# of Sims: 10,000 over 15 years using randomly selected trades based on WL8 sim metrics.				
Total: \$	190,669,620	Sim #: 1	(A: 136, B: 251, C: 231, D: 162)	CAGR: 65.46 %
Total: \$	215,218,349	Sim #: 500	(A: 117, B: 289, C: 220, D: 154)	CAGR: 66.80 %
Total: \$	1,371,815,458	Sim #: 1,000	(A: 133, B: 282, C: 224, D: 141)	CAGR: 88.72 %
Total: \$	433,226,902	Sim #: 1,500	(A: 143, B: 258, C: 218, D: 161)	CAGR: 74.76 %
Total: \$	126,100,646	Sim #: 2,000	(A: 110, B: 273, C: 251, D: 146)	CAGR: 60.96 %
Total: \$	145,192,662	Sim #: 2,500	(A: 128, B: 261, C: 230, D: 161)	CAGR: 62.48 %
Total: \$	64,057,605	Sim #: 3,000	(A: 112, B: 278, C: 228, D: 162)	CAGR: 53.85 %
Total: \$	98,065,217	Sim #: 3,500	(A: 117, B: 277, C: 225, D: 161)	CAGR: 58.28 %
Total: \$	273,567,797	Sim #: 4,000	(A: 123, B: 277, C: 228, D: 152)	CAGR: 69.49 %
Total: \$	170,899,603	Sim #: 4,500	(A: 118, B: 291, C: 211, D: 160)	CAGR: 64.25 %
Total: \$	550,720,883	Sim #: 5,000	(A: 134, B: 261, C: 238, D: 147)	CAGR: 77.58 %
Total: \$	640,098,687	Sim #: 5,500	(A: 139, B: 259, C: 232, D: 150)	CAGR: 79.37 %
Total: \$	505,048,434	Sim #: 6,000	(A: 135, B: 272, C: 218, D: 155)	CAGR: 76.56 %
Total: \$	1,597,826,200	Sim #: 6,500	(A: 143, B: 273, C: 217, D: 147)	CAGR: 90.65 %
Total: \$	7,994,718	Sim #: 7,000	(A: 111, B: 254, C: 232, D: 183)	CAGR: 33.92 %
Total: \$	439,545,490	Sim #: 7,500	(A: 132, B: 267, C: 230, D: 151)	CAGR: 74.93 %
Total: \$	568,974,565	Sim #: 8,000	(A: 131, B: 268, C: 235, D: 146)	CAGR: 77.97 %
Total: \$	182,501,040	Sim #: 8,500	(A: 128, B: 277, C: 210, D: 165)	CAGR: 64.97 %
Total: \$	520,915,650	Sim #: 9,000	(A: 148, B: 253, C: 217, D: 162)	CAGR: 76.92 %
Total: \$	360,014,724	Sim #: 9,500	(A: 136, B: 260, C: 228, D: 156)	CAGR: 72.62 %
Total: \$	430,466,889	Sim #: 10,000	(A: 138, B: 269, C: 213, D: 160)	CAGR: 74.69 %
Average: \$	854,829,785			CAGR: 82.86 %

[\(Click here to enlarge\)](#)

⁸ Refer to the [GRF Equation](#) paper for a copy of the code.

Any change to the trade type distribution is reflected in the outcome of these simulations. Moving one type to another will have repercussions. Equations (1) and (3) are expressions of a product function where each trade becomes important and relevant. Any win or loss will reverberate over the entire return series.

We could shuffle all the WL8 trades in any order and get the same outcome. It is equivalent to stating that a Monte Carlo method without replacements is a trivial pursuit since it would not change any of those outcomes.

Nonetheless, since we randomized the trade selection process based on the WL8 portfolio metrics, we are in a randomly generated Monte Carlo scenario with randomized replacements and unpredictable paths for each simulation from day one.

All the presented scenarios with those 10,000 simulations are composed of randomly generated data. As such, could either represent past as well as future scenarios. Nonetheless, all these scenarios are based on the average portfolio metrics achieved after the 15-year WL8 simulation. Those metrics appear in equation (3).

The above chart shows that the average percent return per trade is expected to remain relatively constant since it is viewed as a continuation of its long-term average obtained over a large number of trades. Even if you have random-like returns with a large number of occurrences, that average might not change that fast, even if you add more trades.

If you have 405 trades with an average return of 0.0452, adding 10 more trades with about the same average might not change the prior achieved average by that much.

MOVING TRADES AROUND

One way of improving the strategy would be to move a Type-D trade to a Type-A.

Displacing a single trade out of 780 would have an impact that can be estimated even before you move the trade. You would get one more Type-A trade and one less Type-D trade.

We already know their attained average returns: $1.082 \cdot (1/(1 - 0.0596)) = 1.1506$. It would improve the overall result by 15.06%.⁹

Just moving one trade could increase overall portfolio performance by 15.06%. This trade change could occur anytime over those 15 years and have the same impact. Whatever the value of your portfolio, at whatever time, that single trade change would raise its value by 15.06%, even if it were the first or last trade you made.

⁹ Type-A trades average 8.2% in profit while Type-D has an average loss of -5.96%.

That was one trade out of 780, not something that should be considered out of this world. We could make the same evaluation for other scenarios where we move trades from one type to another.

Figure #3: 10,000 Simulations (15 years) simulated data with 1 trade move.

of Sims: 10,000 over 15 years using randomly selected trades based on WL8 sim metrics.

Total: \$	3,843,197,764	Sim #:	1	(A: 144, B: 273, C: 229, D: 134)	CAGR:	102.14 %
W/Diff.: \$	4,421,884,284	Sim #:	1	(A: 145, B: 273, C: 229, D: 133)	CAGR:	104.04 %
Total: \$	44,455,962	Sim #:	1,000	(A: 125, B: 256, C: 225, D: 174)	CAGR:	50.15 %
W/Diff.: \$	51,149,884	Sim #:	1,000	(A: 126, B: 256, C: 225, D: 173)	CAGR:	51.56 %
Total: \$	247,267,988	Sim #:	2,000	(A: 140, B: 274, C: 192, D: 174)	CAGR:	68.35 %
W/Diff.: \$	284,500,173	Sim #:	2,000	(A: 141, B: 274, C: 192, D: 173)	CAGR:	69.93 %
Total: \$	243,034,884	Sim #:	3,000	(A: 119, B: 294, C: 210, D: 157)	CAGR:	68.16 %
W/Diff.: \$	279,629,673	Sim #:	3,000	(A: 120, B: 294, C: 210, D: 156)	CAGR:	69.74 %
Total: \$	921,518,064	Sim #:	4,000	(A: 144, B: 258, C: 228, D: 150)	CAGR:	83.78 %
W/Diff.: \$	1,060,274,931	Sim #:	4,000	(A: 145, B: 258, C: 228, D: 149)	CAGR:	85.51 %
Total: \$	1,932,615,094	Sim #:	5,000	(A: 142, B: 280, C: 212, D: 146)	CAGR:	93.08 %
W/Diff.: \$	2,223,617,112	Sim #:	5,000	(A: 143, B: 280, C: 212, D: 145)	CAGR:	94.90 %
Total: \$	207,082,785	Sim #:	6,000	(A: 131, B: 265, C: 223, D: 161)	CAGR:	66.37 %
W/Diff.: \$	238,264,115	Sim #:	6,000	(A: 132, B: 265, C: 223, D: 160)	CAGR:	67.93 %
Total: \$	810,394,702	Sim #:	7,000	(A: 141, B: 272, C: 212, D: 155)	CAGR:	82.21 %
W/Diff.: \$	932,419,255	Sim #:	7,000	(A: 142, B: 272, C: 212, D: 154)	CAGR:	83.92 %
Total: \$	389,852,963	Sim #:	8,000	(A: 134, B: 268, C: 222, D: 156)	CAGR:	73.54 %
W/Diff.: \$	448,554,770	Sim #:	8,000	(A: 135, B: 268, C: 222, D: 155)	CAGR:	75.17 %
Total: \$	338,392,757	Sim #:	9,000	(A: 125, B: 283, C: 218, D: 154)	CAGR:	71.91 %
W/Diff.: \$	389,345,984	Sim #:	9,000	(A: 126, B: 283, C: 218, D: 153)	CAGR:	73.52 %
Total: \$	112,430,758	Sim #:	10,000	(A: 135, B: 269, C: 198, D: 178)	CAGR:	59.73 %
W/Diff.: \$	129,359,932	Sim #:	10,000	(A: 136, B: 269, C: 198, D: 177)	CAGR:	61.23 %
Average	: \$ 846,844,105	CAGR:	82.75 %			
Average + 1 diff.:	\$ 974,356,999	CAGR:	84.47 %			
Average increase : 115.06 % An expected increase of: \$ 127,512,894						

[\(Click here to enlarge\)](#)

We can use the same program structure we had in Figure #4 of the [GRF Equation](#) paper, add a trade move feature, and display the outcome of those randomly generated trade types.

Doing so would give us something like Figure #3, where a single Type-D trade is moved to a Type-A trade (increasing Type-A trades by one).

We made a small move and transformed a Type-D trade into a Type-A. The method is irrelevant. What counts is that over 780 trades, one trade changed type. We had our expected 15.06% increase in the average value for all the 10,000 simulations with an average increase in value of \$127,512,894. It is the mean expected value of changing a single trade from a Type-D to a Type-A; the added profit compounds as any other in the trade series.

How about if we change 5 trades from Type-D to Type-A?

That too, is easy to evaluate. I changed the move count from 1 to 5, and job done.

Following is the outcome of that simulation.

Figure #4: 10,000 Simulations (15 years) with 5 trade moves.

of Sims: 10,000 over 15 years using randomly selected trades based on WL8 sim metrics.

Total:	\$ 1,325,000,157	Sim #:	1	(A: 131, B: 282, C: 228, D: 139)	CAGR:	88.28 %
W/Diff.:	\$ 2,671,708,865	Sim #:	1	(A: 136, B: 282, C: 228, D: 134)	CAGR:	97.30 %
Total:	\$ 649,570,191	Sim #:	1,000	(A: 139, B: 274, C: 210, D: 157)	CAGR:	79.55 %
W/Diff.:	\$ 1,309,782,816	Sim #:	1,000	(A: 144, B: 274, C: 210, D: 152)	CAGR:	88.14 %
Total:	\$ 158,495,775	Sim #:	2,000	(A: 120, B: 279, C: 223, D: 158)	CAGR:	63.43 %
W/Diff.:	\$ 319,588,314	Sim #:	2,000	(A: 125, B: 279, C: 223, D: 153)	CAGR:	71.25 %
Total:	\$ 747,587,303	Sim #:	3,000	(A: 136, B: 295, C: 188, D: 161)	CAGR:	81.24 %
W/Diff.:	\$ 1,507,422,934	Sim #:	3,000	(A: 141, B: 295, C: 188, D: 156)	CAGR:	89.91 %
Total:	\$ 122,021,095	Sim #:	4,000	(A: 113, B: 295, C: 211, D: 161)	CAGR:	60.61 %
W/Diff.:	\$ 246,041,361	Sim #:	4,000	(A: 118, B: 295, C: 211, D: 156)	CAGR:	68.29 %
Total:	\$ 5,264,528,737	Sim #:	5,000	(A: 152, B: 281, C: 204, D: 143)	CAGR:	106.42 %
W/Diff.:	\$ 10,615,310,509	Sim #:	5,000	(A: 157, B: 281, C: 204, D: 138)	CAGR:	116.30 %
Total:	\$ 231,430,997	Sim #:	6,000	(A: 128, B: 256, C: 245, D: 151)	CAGR:	67.61 %
W/Diff.:	\$ 466,653,716	Sim #:	6,000	(A: 133, B: 256, C: 245, D: 146)	CAGR:	75.63 %
Total:	\$ 383,963,165	Sim #:	7,000	(A: 133, B: 266, C: 227, D: 154)	CAGR:	73.36 %
W/Diff.:	\$ 774,217,110	Sim #:	7,000	(A: 138, B: 266, C: 227, D: 149)	CAGR:	81.66 %
Total:	\$ 150,319,139	Sim #:	8,000	(A: 135, B: 256, C: 222, D: 167)	CAGR:	62.85 %
W/Diff.:	\$ 303,101,078	Sim #:	8,000	(A: 140, B: 256, C: 222, D: 162)	CAGR:	70.65 %
Total:	\$ 445,334,662	Sim #:	9,000	(A: 133, B: 271, C: 222, D: 154)	CAGR:	75.08 %
W/Diff.:	\$ 897,965,602	Sim #:	9,000	(A: 138, B: 271, C: 222, D: 149)	CAGR:	83.46 %
Total:	\$ 343,008,913	Sim #:	10,000	(A: 142, B: 259, C: 215, D: 164)	CAGR:	72.06 %
W/Diff.:	\$ 691,637,618	Sim #:	10,000	(A: 147, B: 259, C: 215, D: 159)	CAGR:	80.30 %
Average	: \$ 875,938,940	CAGR:	83.16 %			
Average + 5 diff.:	\$ 1,766,229,097	CAGR:	91.93 %			
Average increase :	201.64 %	An expected increase of:	\$ 890,290,157			

[\(Click here to enlarge\)](#)

Changing 5 Type-D trades into Type-A trades, whatever the method used represent an increase of 201.64% $((1.082 \cdot (1/(1 - 0.0596)))^5 = 2.0164)$. Moving only 5 trades out of 780 doubled the portfolio's outcome. The method used to change one Type-D trade into a Type-A trade could be the same process applied 5 times or more.

It puts a value on the opportunity cost of not seeking the method to convert those trades from Type-D to Type-A.

Changing those 5 trades out of 780 might result in an expected increase of \$890,290,157. Should we consider the effort to improve the trading strategy worthwhile? I hope that Figures #3 and #4 above answer that question.

It would be even more impressive if you changed 10 Type-D trades into Type-A ones. Should you need more motivation to make those modifications to the program to reach that goal, see Figure #5, which has the simulation result.

I moved 10 of the average trades from the Type-D to Type-A average trades. It increases the overall portfolio average return by 406.58%. In numbers, it represented an increase of \$2,672,991,152, which might again represent an incentive to seek those 10 trade moves out of the 780.

In these three simulations (Figures #3, #4, and #5), I showed the simulation with and without the trade moves. The 'W/Diff.' line shows the trade type change from Type-D

to Type-A. We are not talking about making extreme moves. Ten trades out of 780 is only 1.28% of total trades. I am only stressing the opportunity cost of not seeking those program modifications.

Figure #5: 10,000 Simulations (15 years) with 10 trade type moves.

of Sims: 10,000 over 15 years using randomly selected trades based on WL8 sim metrics.

Total: \$	272,166,174	Sim #:	1	(A: 136, B: 263, C: 219, D: 162)	CAGR:	69.43 %
W/Diff.: \$	1,106,574,227	Sim #:	1	(A: 146, B: 263, C: 219, D: 152)	CAGR:	86.04 %
Total: \$	59,596,395	Sim #:	1,000	(A: 122, B: 278, C: 204, D: 176)	CAGR:	53.11 %
W/Diff.: \$	242,307,242	Sim #:	1,000	(A: 132, B: 278, C: 204, D: 166)	CAGR:	68.12 %
Total: \$	346,872,928	Sim #:	2,000	(A: 148, B: 231, C: 243, D: 158)	CAGR:	72.19 %
W/Diff.: \$	1,410,317,221	Sim #:	2,000	(A: 158, B: 231, C: 243, D: 148)	CAGR:	89.07 %
Total: \$	529,349,061	Sim #:	3,000	(A: 141, B: 268, C: 211, D: 160)	CAGR:	77.11 %
W/Diff.: \$	2,152,229,351	Sim #:	3,000	(A: 151, B: 268, C: 211, D: 150)	CAGR:	94.47 %
Total: \$	2,744,079,874	Sim #:	4,000	(A: 134, B: 282, C: 233, D: 131)	CAGR:	97.65 %
W/Diff.: \$	11,156,890,012	Sim #:	4,000	(A: 144, B: 282, C: 233, D: 121)	CAGR:	117.02 %
Total: \$	1,681,414,069	Sim #:	5,000	(A: 153, B: 244, C: 238, D: 145)	CAGR:	91.30 %
W/Diff.: \$	6,836,299,487	Sim #:	5,000	(A: 163, B: 244, C: 238, D: 135)	CAGR:	110.05 %
Total: \$	480,186,410	Sim #:	6,000	(A: 131, B: 283, C: 210, D: 156)	CAGR:	75.97 %
W/Diff.: \$	1,952,343,666	Sim #:	6,000	(A: 141, B: 283, C: 210, D: 146)	CAGR:	93.21 %
Total: \$	198,312,375	Sim #:	7,000	(A: 129, B: 273, C: 215, D: 163)	CAGR:	65.89 %
W/Diff.: \$	806,299,179	Sim #:	7,000	(A: 139, B: 273, C: 215, D: 153)	CAGR:	82.15 %
Total: \$	1,104,210,686	Sim #:	8,000	(A: 146, B: 265, C: 216, D: 153)	CAGR:	86.01 %
W/Diff.: \$	4,489,503,857	Sim #:	8,000	(A: 156, B: 265, C: 216, D: 143)	CAGR:	104.24 %
Total: \$	924,994,367	Sim #:	9,000	(A: 138, B: 272, C: 221, D: 149)	CAGR:	83.83 %
W/Diff.: \$	3,760,845,489	Sim #:	9,000	(A: 148, B: 272, C: 221, D: 139)	CAGR:	101.85 %
Total: \$	1,034,858,500	Sim #:	10,000	(A: 133, B: 287, C: 212, D: 148)	CAGR:	85.21 %
W/Diff.: \$	4,207,531,485	Sim #:	10,000	(A: 143, B: 287, C: 212, D: 138)	CAGR:	103.36 %

Average	:	\$	871,872,906	CAGR:	83.10 %
Average + 10 diff.:	:	\$	3,544,864,058	CAGR:	101.05 %

Average increase : 406.58 % An expected increase of: \$2,672,991,152

[\(Click here to enlarge\)](#)

Hopefully, I put enough on the table to motivate you to seek program modifications that could not only matter but will matter in a big way. A minor change in the perception of the program, and you could reap tremendous rewards.

We could have determined the outcome of the above simulations beforehand since we have their average impact on the equation.

For the 10 trade case, we have: $(1.082 \cdot (1/(1 - 0.0596)))^{10} = 4.0658$, or a 406.58% increase, which corresponds to the average increase in Figure #5. It did not matter which scenario you took out of the 10,000 simulations; making those trade-type moves would have increased overall performance.

One easy program modification would be to move Type-D trades to Type-C. The move could simply ignore and bypass some of those Type-D trades. Moving a single trade of Type-D to a Type-C trade would raise the outcome by 6.3%. And if you do this for ten trades, you should increase the overall average portfolio by 84.87% ($((1/(1 - 0.0596)))^{10} = 1.8487$).

Because you know the composition of your strategy's portfolio equation, you can

make projections and even study the impact of trading procedure modifications. As shown above, bypassing some Type-D trades is sufficient to convert them into Type-C trades since they generate no profits and do not show a loss either.

It should not be that big a task to bypass 10 trades out of the expected 156 Type-D trades; they represent only 6.4% of the total.

Figure #6: 10,000 Simulations (15 years) with 10 moves from Type-D to Type-C.

of Sims: 10,000 over 15 years using randomly selected trades based on WL8 sim metrics.

Total: \$	3,630,644,728	Sim #:	1	(A: 140, B: 290, C: 212, D: 138)	CAGR:	101.37 %
W/Diff.: \$	6,712,086,569	Sim #:	1	(A: 140, B: 290, C: 222, D: 128)	CAGR:	109.79 %
Total: \$	562,924,080	Sim #:	1,000	(A: 131, B: 278, C: 220, D: 151)	CAGR:	77.84 %
W/Diff.: \$	1,040,695,369	Sim #:	1,000	(A: 131, B: 278, C: 230, D: 141)	CAGR:	85.28 %
Total: \$	363,495,500	Sim #:	2,000	(A: 134, B: 276, C: 209, D: 161)	CAGR:	72.73 %
W/Diff.: \$	672,005,511	Sim #:	2,000	(A: 134, B: 276, C: 219, D: 151)	CAGR:	79.95 %
Total: \$	376,741,144	Sim #:	3,000	(A: 138, B: 250, C: 239, D: 153)	CAGR:	73.14 %
W/Diff.: \$	696,493,147	Sim #:	3,000	(A: 138, B: 250, C: 249, D: 143)	CAGR:	80.38 %
Total: \$	372,466,580	Sim #:	4,000	(A: 121, B: 272, C: 245, D: 142)	CAGR:	73.01 %
W/Diff.: \$	688,590,628	Sim #:	4,000	(A: 121, B: 272, C: 255, D: 132)	CAGR:	80.25 %
Total: \$	1,087,857,499	Sim #:	5,000	(A: 136, B: 289, C: 203, D: 152)	CAGR:	85.83 %
W/Diff.: \$	2,011,156,214	Sim #:	5,000	(A: 136, B: 289, C: 213, D: 142)	CAGR:	93.60 %
Total: \$	254,456,400	Sim #:	6,000	(A: 127, B: 266, C: 234, D: 153)	CAGR:	68.67 %
W/Diff.: \$	470,421,512	Sim #:	6,000	(A: 127, B: 266, C: 244, D: 143)	CAGR:	75.72 %
Total: \$	4,847,380,983	Sim #:	7,000	(A: 152, B: 272, C: 216, D: 140)	CAGR:	105.29 %
W/Diff.: \$	8,961,504,975	Sim #:	7,000	(A: 152, B: 272, C: 226, D: 130)	CAGR:	113.87 %
Total: \$	173,892,534	Sim #:	8,000	(A: 119, B: 291, C: 209, D: 161)	CAGR:	64.44 %
W/Diff.: \$	321,480,571	Sim #:	8,000	(A: 119, B: 291, C: 219, D: 151)	CAGR:	71.32 %
Total: \$	244,911,636	Sim #:	9,000	(A: 132, B: 268, C: 219, D: 161)	CAGR:	68.24 %
W/Diff.: \$	452,775,809	Sim #:	9,000	(A: 132, B: 268, C: 229, D: 151)	CAGR:	75.28 %
Total: \$	99,356,816	Sim #:	10,000	(A: 118, B: 281, C: 217, D: 164)	CAGR:	58.42 %
W/Diff.: \$	183,684,055	Sim #:	10,000	(A: 118, B: 281, C: 227, D: 154)	CAGR:	65.05 %
Average	: \$ 845,057,669	CAGR:	82.72 %			
Average + 10 diff.:	\$ 1,562,284,568	CAGR:	90.36 %			
Average increase	: 184.87 %	An expected increase of:	\$ 717,226,899			

[\(Click here to enlarge\)](#)

It is here where AI could help select those trades that could be bypassed or ignored. Increasing Type-C trades has no impact, except that the increase has to come from the other trade types, either increasing or reducing the overall outcome.

Regardless, from equation (3), we could extract all types of variations on the same theme. Increasing one or two of the trade types while reducing one or two of the non-productive types (Type-D and Type-C). You want to keep all trades of Type-A and Type-B. However, you are not against improving their average percent return per trade. That too would have a measurable impact over the long term.

Figures #2 to #6 can attest to the wide range of outcomes. You might not be able to predict the future. However, with equation (3), you can know in advance what your improvements to the strategy could bring.

Going back to Figure #5, where we have 10 trades of Type-D moved to Type-A by some added trading rules, we could look at the impact of adding one or two years to

the scenario and see the overall effect. Such a simulation is easy: you add 52 trades to N to add one more year.

We should compare Figure #7 to Figure #5. The simulations were performed under the same conditions. In Figure #7, we added one more year of trading in the same fashion the strategy had done over its previous 15 years.

Figure #7: 10,000 Simulations (16 years) with 10 moves from D to A.

of Sims: 10,000 over 16 years using randomly selected trades based on WL8 sim metrics.

Total: \$	761,032,971	Sim #:	1	(A: 153, B: 267, C: 243, D: 169)	CAGR:	74.82 %
W/Diff.: \$	3,094,210,646	Sim #:	1	(A: 163, B: 267, C: 243, D: 159)	CAGR:	90.84 %
Total: \$	237,876,813	Sim #:	1,000	(A: 134, B: 299, C: 220, D: 179)	CAGR:	62.56 %
W/Diff.: \$	967,160,420	Sim #:	1,000	(A: 144, B: 299, C: 220, D: 169)	CAGR:	77.46 %
Total: \$	105,761,864	Sim #:	2,000	(A: 126, B: 295, C: 231, D: 180)	CAGR:	54.53 %
W/Diff.: \$	430,006,976	Sim #:	2,000	(A: 136, B: 295, C: 231, D: 170)	CAGR:	68.69 %
Total: \$	264,569,822	Sim #:	3,000	(A: 130, B: 307, C: 219, D: 176)	CAGR:	63.65 %
W/Diff.: \$	1,075,688,952	Sim #:	3,000	(A: 140, B: 307, C: 219, D: 166)	CAGR:	78.64 %
Total: \$	369,062,709	Sim #:	4,000	(A: 140, B: 273, C: 252, D: 167)	CAGR:	67.09 %
W/Diff.: \$	1,500,536,514	Sim #:	4,000	(A: 150, B: 273, C: 252, D: 157)	CAGR:	82.40 %
Total: \$	15,349,666	Sim #:	5,000	(A: 136, B: 251, C: 242, D: 203)	CAGR:	36.97 %
W/Diff.: \$	62,408,730	Sim #:	5,000	(A: 146, B: 251, C: 242, D: 193)	CAGR:	49.52 %
Total: \$	134,260,925	Sim #:	6,000	(A: 124, B: 298, C: 235, D: 175)	CAGR:	56.85 %
W/Diff.: \$	545,878,562	Sim #:	6,000	(A: 134, B: 298, C: 235, D: 165)	CAGR:	71.23 %
Total: \$	127,889,205	Sim #:	7,000	(A: 124, B: 286, C: 252, D: 170)	CAGR:	56.38 %
W/Diff.: \$	519,972,398	Sim #:	7,000	(A: 134, B: 286, C: 252, D: 160)	CAGR:	70.71 %
Total: \$	610,529,400	Sim #:	8,000	(A: 138, B: 287, C: 244, D: 163)	CAGR:	72.43 %
W/Diff.: \$	2,482,292,672	Sim #:	8,000	(A: 148, B: 287, C: 244, D: 153)	CAGR:	88.23 %
Total: \$	357,122,959	Sim #:	9,000	(A: 143, B: 295, C: 212, D: 182)	CAGR:	66.74 %
W/Diff.: \$	1,451,991,838	Sim #:	9,000	(A: 153, B: 295, C: 212, D: 172)	CAGR:	82.02 %
Total: \$	3,103,502,479	Sim #:	10,000	(A: 150, B: 283, C: 249, D: 150)	CAGR:	90.87 %
W/Diff.: \$	12,618,231,758	Sim #:	10,000	(A: 160, B: 283, C: 249, D: 140)	CAGR:	108.36 %
Average	: \$ 1,584,103,485	CAGR:	83.01 %			
Average + 10 diff.:	\$ 6,440,653,759	CAGR:	99.78 %			
Average increase :	406.58 %	An expected increase of:	\$4,856,550,273			

[\(Click here to enlarge\)](#)

The increase in performance was again as in Figure #5: 406.58%. By adding one year to the trading strategy, the total outcome increased to \$4,856,550,273 from \$2,672,991,152.

In the first year or two, the outcome difference was not consequential. However, this added year at the end of the time series is a serious reason for the quest to improve the strategy in this manner. You know what your code modification might bring to the strategy's long-term return.

It should also be expected that this thing would fly if we added another year. To make this case, I only need to change one number and add another 52 trades to N . See the result in Figure #8 below.

The average increase was again 406.58%. But now, the expected gain over the base line is \$9,816,753,852.

Figure #8: 10,000 Simulations (17 years) with 10 moves from D to A.

# of Sims: 10,000 over 17 years using randomly selected trades based on WL8 sim metrics.						
Total: \$	5,774,060,914	Sim #:	1	(A: 161, B: 312, C: 243, D: 168)	CAGR:	90.58 %
W/Diff.: \$	23,476,198,036	Sim #:	1	(A: 171, B: 312, C: 243, D: 158)	CAGR:	106.98 %
Total: \$	601,556,999	Sim #:	1,000	(A: 159, B: 297, C: 233, D: 195)	CAGR:	66.84 %
W/Diff.: \$	2,445,812,654	Sim #:	1,000	(A: 169, B: 297, C: 233, D: 185)	CAGR:	81.19 %
Total: \$	836,282,578	Sim #:	2,000	(A: 156, B: 285, C: 263, D: 180)	CAGR:	70.11 %
W/Diff.: \$	3,400,160,770	Sim #:	2,000	(A: 166, B: 285, C: 263, D: 170)	CAGR:	84.74 %
Total: \$	2,808,275,255	Sim #:	3,000	(A: 155, B: 314, C: 242, D: 173)	CAGR:	82.67 %
W/Diff.: \$	11,417,895,828	Sim #:	3,000	(A: 165, B: 314, C: 242, D: 163)	CAGR:	98.38 %
Total: \$	535,001,286	Sim #:	4,000	(A: 152, B: 293, C: 253, D: 186)	CAGR:	65.70 %
W/Diff.: \$	2,175,210,191	Sim #:	4,000	(A: 162, B: 293, C: 253, D: 176)	CAGR:	79.95 %
Total: \$	343,176,336	Sim #:	5,000	(A: 149, B: 286, C: 263, D: 186)	CAGR:	61.43 %
W/Diff.: \$	1,395,287,607	Sim #:	5,000	(A: 159, B: 286, C: 263, D: 176)	CAGR:	75.31 %
Total: \$	2,227,599,319	Sim #:	6,000	(A: 158, B: 292, C: 264, D: 170)	CAGR:	80.20 %
W/Diff.: \$	9,056,981,478	Sim #:	6,000	(A: 168, B: 292, C: 264, D: 160)	CAGR:	95.70 %
Total: \$	628,672,238	Sim #:	7,000	(A: 158, B: 297, C: 236, D: 193)	CAGR:	67.28 %
W/Diff.: \$	2,556,057,892	Sim #:	7,000	(A: 168, B: 297, C: 236, D: 183)	CAGR:	81.66 %
Total: \$	558,104,095	Sim #:	8,000	(A: 137, B: 326, C: 239, D: 182)	CAGR:	66.11 %
W/Diff.: \$	2,269,141,678	Sim #:	8,000	(A: 147, B: 326, C: 239, D: 172)	CAGR:	80.40 %
Total: \$	1,345,199,537	Sim #:	9,000	(A: 148, B: 314, C: 246, D: 176)	CAGR:	74.93 %
W/Diff.: \$	5,469,317,210	Sim #:	9,000	(A: 158, B: 314, C: 246, D: 166)	CAGR:	89.98 %
Total: \$	577,648,476	Sim #:	10,000	(A: 148, B: 300, C: 253, D: 183)	CAGR:	66.45 %
W/Diff.: \$	2,348,605,292	Sim #:	10,000	(A: 158, B: 300, C: 253, D: 173)	CAGR:	80.76 %
Average : \$ 3,202,016,476 CAGR: 84.09 %						
Average + 10 diff.: \$ 13,018,770,328 CAGR: 99.92 %						
Average increase : 406.58 % An expected increase of: \$9,816,753,852						

[\(Click here to enlarge\)](#)

That is the prize at the end of the rainbow.

This increased outcome results from your modified trading procedures and adding those two years to the first 15 years of trading.

We should have long-term visions of what we intend to do and find ways to execute them.

My version of this trading strategy is so simple that anyone could do it. Finding the program modifications might be considered something else, but they should not be difficult to find and execute. We make simulations to determine if our strategies could survive over past or simulated market data. In this case, we simulated on trade distributions.

THE BUY & HOLD SCENE

Anyone deciding to put some of their money in the stock market with the intention to hold for 20+ years is making a bet, directly or indirectly, on the future and prosperity of a small or large group of stocks.

As such, a buy-and-hold strategy becomes an all-in scenario. Every day, your money is on the line, and it stays there for years on end. Your investment can even be held

while in retirement, from which you can withdraw some benefits should you want to.¹⁰

We have no technical advantage of buying the open on the first trading day of the week and selling on Friday's close. The outcome tends to the long-term return a buy-and-hold strategy would give. It should be less since we have a long-term average gain between Friday's close and the following Monday's open. Many academic papers have done those simulations and shown the same point over the years.

There should not be much return difference between a buy-and-hold on SPY and weekly buying SPY on Monday's opening and selling it on Friday's close. Nonetheless, there is one.

The OPPW strategy's trading rules play on TQQQ's weekly variance. As mentioned before, these are not complicated trading rules. Only 4 types of trades can come out of it, as depicted in Figure #1. SPY cannot provide that many 7% weekly moves; it does not have the same variance level TQQQ has.

Whatever the trade using the OPPW strategy, it will fall into one of the four trade types. For example, if the weekly positive volatility for QQQ is higher than 2.35% to 2.75%+, you will get a Type-A trade. There were 135 of those trades out of 782 in the WL8 simulation, some 17.26% of the total trades (see Table #2 above).¹¹

The distribution of those trade types varies in number as if the classification barriers were randomly moving as the number of trades increased. Nonetheless, the trade type delimiters would tend to their long-term averages. It is something we see in all the simulations and trade-type variations. A trade type starts where another finishes.

One point about the simulations in Figures #2 to #8 is that each of the 10,000 simulations series used the simulation program provided in the OPPW article.¹² Each simulation in the series of 10,000 simulations was unique and followed the program script.

Figures #3 to #8 provided a before and after moving several trades from one trade type to another. It evaluates the improvements made. We could have determined the outcome before the simulations; it was all related to equation (3).

As presented after Figure #5, we had: $(1.082 \cdot (1/(1 - 0.0596)))^{10} = 4.0658$, the same 406.58% increase as in Figure #8. Moving 10 trades from Type-D to Type-A, we added 10 trades hitting their profit targets and eliminated 10 trades with their average losses. Removing the Type-D trades was the same as not having them, so we had to compensate as if it did not happen, the reason for the compensation factor

¹⁰ By cashing in some shares or receiving dividends.

¹¹ Was presented as Table #1 in [One Percent Per Week Strategy: Some Trading Habits](#).

¹² See Figure #4 in [The One Percent Per Week TQQQ Trading Strategy: MY EQUATION](#).

$1/(1 - 0.0596)$ in the equation.

Nonetheless, we still do not know which scenario will happen in the future. However, we have a wide range of estimated outcomes.

We should consider the average of those scenarios as the most expected future outcome from all those simulations. Figure #18 of my *GRF Equation* reached the same conclusion.

OTHER IMPROVEMENTS

We can improve this strategy further by increasing its hit rate or reducing the average percent loss per losing trade. What would be needed are new trading rules having, on average, the desired impact.

Doing the same test as in Figure #5 and improving the average percent win or loss per trade could have quite an impact.

The improvement need not be large. A slight 5% improvement on the average percent win per winning trade would push the average win percent from 0.082 to 0.0861. A less than half of 1% difference. To show its impact, see the corresponding 10,000 simulations with that scenario (Figure #9).

Figure #9: 10,000 Simulations With 10 Type-D to A, Type-A +5% Improvement.

of Sims: 10,000 over 15 years using randomly selected trades based on WL8 sim metrics.

Total: \$	257,795,747	Sim #:	1	(A: 138, B: 260, C: 218, D: 164)	CAGR:	68.82 %
W/Diff.: \$	1,834,509,584	Sim #:	1	(A: 148, B: 260, C: 218, D: 154)	CAGR:	92.41 %
Total: \$	1,730,656,586	Sim #:	1,000	(A: 151, B: 242, C: 246, D: 141)	CAGR:	91.67 %
W/Diff.: \$	12,936,247,720	Sim #:	1,000	(A: 161, B: 242, C: 246, D: 131)	CAGR:	119.17 %
Total: \$	117,722,737	Sim #:	2,000	(A: 128, B: 256, C: 234, D: 162)	CAGR:	60.22 %
W/Diff.: \$	806,638,708	Sim #:	2,000	(A: 138, B: 256, C: 234, D: 152)	CAGR:	82.16 %
Total: \$	96,093,319	Sim #:	3,000	(A: 119, B: 271, C: 229, D: 161)	CAGR:	58.07 %
W/Diff.: \$	636,398,170	Sim #:	3,000	(A: 129, B: 271, C: 229, D: 151)	CAGR:	79.30 %
Total: \$	234,669,967	Sim #:	4,000	(A: 126, B: 268, C: 232, D: 154)	CAGR:	67.76 %
W/Diff.: \$	1,595,846,492	Sim #:	4,000	(A: 136, B: 268, C: 232, D: 144)	CAGR:	90.63 %
Total: \$	117,468,547	Sim #:	5,000	(A: 133, B: 253, C: 227, D: 167)	CAGR:	60.20 %
W/Diff.: \$	820,262,897	Sim #:	5,000	(A: 143, B: 253, C: 227, D: 157)	CAGR:	82.36 %
Total: \$	3,276,579,018	Sim #:	6,000	(A: 143, B: 291, C: 202, D: 144)	CAGR:	100.00 %
W/Diff.: \$	23,761,707,558	Sim #:	6,000	(A: 153, B: 291, C: 202, D: 134)	CAGR:	128.24 %
Total: \$	165,366,832	Sim #:	7,000	(A: 130, B: 258, C: 232, D: 160)	CAGR:	63.89 %
W/Diff.: \$	1,141,700,573	Sim #:	7,000	(A: 140, B: 258, C: 232, D: 150)	CAGR:	86.42 %
Total: \$	318,498,429	Sim #:	8,000	(A: 112, B: 301, C: 220, D: 147)	CAGR:	71.21 %
W/Diff.: \$	2,054,211,495	Sim #:	8,000	(A: 122, B: 301, C: 220, D: 137)	CAGR:	93.87 %
Total: \$	640,619,643	Sim #:	9,000	(A: 136, B: 267, C: 227, D: 150)	CAGR:	79.38 %
W/Diff.: \$	4,524,383,202	Sim #:	9,000	(A: 146, B: 267, C: 227, D: 140)	CAGR:	104.35 %
Total: \$	660,546,495	Sim #:	10,000	(A: 154, B: 272, C: 179, D: 175)	CAGR:	79.75 %
W/Diff.: \$	4,993,769,299	Sim #:	10,000	(A: 164, B: 272, C: 179, D: 165)	CAGR:	105.70 %

Average : \$ 853,195,974 CAGR: 82.84 %
Average + 10 diff.: \$ 6,174,327,140 CAGR: 108.63 %

Average increase : 723.67 % An expected increase of: \$5,321,131,166

[\(Click here to enlarge\)](#)

The before line (Total) in Figure #9 averages about the same as in Figure #5. The average CAGR went from 83.10% to 82.84%. However, once the 5% improvement is made to the average percent win per winning trade (see the 'W/Diff.' line), the overall CAGR jumps to 108.63%. It increased the bottom line by 5.3 billion compared with the 2.6 billion in Figure #5, where only 10 Type-D trades were moved to Type-A.

A 74% increase in total return \$6,174,327,140 compared to the \$3,544,864,058 of Figure #5. It is all due to the small increase in the average percent win per winning trade, as mentioned above, going from 8.20% to 8.61%.

All Type-A trades respond to the profit target: a single number hard-coded in the trading script. Some added trading procedures will be needed to increase the average win percentage of those Type-A trades by 5%.

To make the point even more explicit, I made another simulation, improving the average percent win per winning trade by 10%. Thereby moving the needle for the average win per winning trade from 8.20% to 9.02% (Refer to Figure #10 below).

The before scenario (Total line) is similar to Figure #5 and generated, on average, an 82.64% CAGR. In comparison, the 10% improvement (the 9.02% average profit target) increased performance to a 116.55% CAGR.

Figure #10: 10,000 Simulations With 10 D to A, Type-A +10% Improvement.

# of Sims: 10,000 over 15 years using randomly selected trades based on WL8 sim metrics.						
Total: \$	53,182,834	Sim #:	1	(A: 133, B: 247, C: 223, D: 177)	CAGR:	51.96 %
W/Diff.: \$	636,506,731	Sim #:	1	(A: 143, B: 247, C: 223, D: 167)	CAGR:	79.30 %
Total: \$	1,024,377,239	Sim #:	1,000	(A: 139, B: 279, C: 210, D: 152)	CAGR:	85.08 %
W/Diff.: \$	12,828,177,036	Sim #:	1,000	(A: 149, B: 279, C: 210, D: 142)	CAGR:	119.05 %
Total: \$	203,083,908	Sim #:	2,000	(A: 130, B: 267, C: 222, D: 161)	CAGR:	66.15 %
W/Diff.: \$	2,376,130,471	Sim #:	2,000	(A: 140, B: 267, C: 222, D: 151)	CAGR:	95.76 %
Total: \$	1,348,893,886	Sim #:	3,000	(A: 138, B: 264, C: 239, D: 139)	CAGR:	88.51 %
W/Diff.: \$	16,765,012,966	Sim #:	3,000	(A: 148, B: 264, C: 239, D: 129)	CAGR:	122.99 %
Total: \$	1,653,935,471	Sim #:	4,000	(A: 134, B: 267, C: 247, D: 132)	CAGR:	91.09 %
W/Diff.: \$	19,944,768,566	Sim #:	4,000	(A: 144, B: 267, C: 247, D: 122)	CAGR:	125.59 %
Total: \$	903,765,308	Sim #:	5,000	(A: 133, B: 270, C: 235, D: 142)	CAGR:	83.54 %
W/Diff.: \$	10,816,510,833	Sim #:	5,000	(A: 143, B: 270, C: 235, D: 132)	CAGR:	116.57 %
Total: \$	309,997,497	Sim #:	6,000	(A: 128, B: 270, C: 229, D: 153)	CAGR:	70.91 %
W/Diff.: \$	3,572,688,287	Sim #:	6,000	(A: 138, B: 270, C: 229, D: 143)	CAGR:	101.16 %
Total: \$	22,827,422	Sim #:	7,000	(A: 112, B: 266, C: 229, D: 173)	CAGR:	43.63 %
W/Diff.: \$	233,147,704	Sim #:	7,000	(A: 122, B: 266, C: 229, D: 163)	CAGR:	67.69 %
Total: \$	297,413,905	Sim #:	8,000	(A: 135, B: 250, C: 242, D: 153)	CAGR:	70.43 %
W/Diff.: \$	3,613,687,775	Sim #:	8,000	(A: 145, B: 250, C: 242, D: 143)	CAGR:	101.31 %
Total: \$	13,577,621,900	Sim #:	9,000	(A: 143, B: 312, C: 194, D: 131)	CAGR:	119.88 %
W/Diff.: \$	175,244,502,447	Sim #:	9,000	(A: 153, B: 312, C: 194, D: 121)	CAGR:	160.76 %
Total: \$	34,535,309	Sim #:	10,000	(A: 134, B: 236, C: 230, D: 180)	CAGR:	47.64 %
W/Diff.: \$	416,460,466	Sim #:	10,000	(A: 144, B: 236, C: 230, D: 170)	CAGR:	74.30 %
Average : \$ 839,348,179 CAGR: 82.64 %						
Average + 10 diff.: \$ 10,801,686,363 CAGR: 116.55 %						
Average increase : 1,286.91 % An expected increase of: \$9,962,338,184						

[\(Click here to enlarge\)](#)

Those are impressive numbers, yet we only made small changes to the trading script.

I was not hoping that the strategy would show some profits. It was knowing, in advance, that it was measurable.

All the simulations could have been evaluated beforehand using equation (3). Furthermore, to get the portfolio metrics used, only one simulation on my version of the WL8 OPPW script was sufficient (see needed variables in Table #1).

Figure #11: 10,000 Simulations With 10 D to A, Type-A +10%, Type-D -5%.

# of Sims: 10,000 over 15 years using randomly selected trades based on WL8 sim metrics.					
Total: \$	1,200,908,814	Sim #:	1	(A: 134, B: 279, C: 224, D: 143)	CAGR: 87.05 %
W/Diff.: \$	22,058,113,711	Sim #:	1	(A: 144, B: 279, C: 224, D: 133)	CAGR: 127.11 %
Total: \$	101,965,198	Sim #:	1,000	(A: 119, B: 273, C: 227, D: 161)	CAGR: 58.70 %
W/Diff.: \$	1,770,350,872	Sim #:	1,000	(A: 129, B: 273, C: 227, D: 151)	CAGR: 91.96 %
Total: \$	122,407,344	Sim #:	2,000	(A: 125, B: 257, C: 240, D: 158)	CAGR: 60.64 %
W/Diff.: \$	2,202,755,155	Sim #:	2,000	(A: 135, B: 257, C: 240, D: 148)	CAGR: 94.77 %
Total: \$	59,168,561	Sim #:	3,000	(A: 120, B: 281, C: 204, D: 175)	CAGR: 53.04 %
W/Diff.: \$	1,081,966,792	Sim #:	3,000	(A: 130, B: 281, C: 204, D: 165)	CAGR: 85.76 %
Total: \$	2,585,874,977	Sim #:	4,000	(A: 149, B: 265, C: 223, D: 143)	CAGR: 96.87 %
W/Diff.: \$	53,192,403,723	Sim #:	4,000	(A: 159, B: 265, C: 223, D: 133)	CAGR: 140.84 %
Total: \$	926,220,477	Sim #:	5,000	(A: 141, B: 262, C: 229, D: 148)	CAGR: 83.84 %
W/Diff.: \$	18,221,971,253	Sim #:	5,000	(A: 151, B: 262, C: 229, D: 138)	CAGR: 124.24 %
Total: \$	852,333,595	Sim #:	6,000	(A: 150, B: 256, C: 216, D: 158)	CAGR: 82.83 %
W/Diff.: \$	18,524,277,635	Sim #:	6,000	(A: 160, B: 256, C: 216, D: 148)	CAGR: 124.48 %
Total: \$	746,025,218	Sim #:	7,000	(A: 130, B: 257, C: 258, D: 135)	CAGR: 81.21 %
W/Diff.: \$	12,962,949,353	Sim #:	7,000	(A: 140, B: 257, C: 258, D: 125)	CAGR: 119.20 %
Total: \$	800,957,575	Sim #:	8,000	(A: 133, B: 268, C: 236, D: 143)	CAGR: 82.07 %
W/Diff.: \$	14,601,212,940	Sim #:	8,000	(A: 143, B: 268, C: 236, D: 133)	CAGR: 120.95 %
Total: \$	32,696,651	Sim #:	9,000	(A: 120, B: 261, C: 224, D: 175)	CAGR: 47.11 %
W/Diff.: \$	597,896,744	Sim #:	9,000	(A: 130, B: 261, C: 224, D: 165)	CAGR: 78.56 %
Total: \$	376,539,834	Sim #:	10,000	(A: 137, B: 263, C: 222, D: 158)	CAGR: 73.14 %
W/Diff.: \$	7,418,509,918	Sim #:	10,000	(A: 147, B: 263, C: 222, D: 148)	CAGR: 111.20 %
Average : \$ 863,575,015 CAGR: 82.99 %					
Average + 10 diff.: \$ 17,058,069,348 CAGR: 123.25 %					

Average increase : 1,975.29 % An expected increase of: \$16,194,494,333

[\(Click here to enlarge\)](#)

We could push even further and request that the average percent loss per losing trades be reduced by 5%. Again, not a significant move. The average percent loss per losing trade would go from - 5.96% to - 5.66%. Again, a small change. Nonetheless, it does have some impact.

We are in a compounding return environment with an all-in trading mentality. As given in equation (1), all the returns in the series matter. We have a product equation: $\prod_1^N \cdot (1 \pm r_i) = (1 + \bar{g})^t$. Also given, in equation (1), we could separate the positive and negative returns:

$$\prod_1^N \cdot (1 \pm r_i) = (1 + \bar{g})^t = (1 + \bar{r}_+)^{N-\lambda} \cdot (1 - \bar{r}_-)^{\lambda}$$

The trade types were the result of the applied trading rules.

Type-A trades occur when their first stopping time is reached. It is dependent on the TQQQ weekly variance. If TQQQ does not swing enough, there is no Type-A trade

for that week. If, during the week, the volatility is sufficient to hit the profit target, the trading script will sell the position at its limit-sell order price. No Type-A trades can register a loss. It can only fall in the Type-A trade if the profit target is hit; otherwise, it becomes one of the other trade types by the close on Friday at the latest.

What these simulations show is that the improvements need not be extraordinary.

Small increments in the important averaged portfolio metrics can do the job over the long term.

The task is not to win next week but to achieve an average overall portfolio return way above market averages over the long term.

If you want to outperform the markets, you have to do things that others might not even consider. Trading TQQQ every week should generate about 3x more than the results you could obtain using QQQ. You are setting the bar low at a long-term average CAGR of about 45%+.

However, holding TQQQ outright, as in a buy-and-hold scenario, could cause your portfolio to have significantly large drawdowns. And we need to alleviate those drawdowns as much as we possibly can.

The small changes made to these trading scenarios were minimal. However, they were well-positioned and well-applied.

All these moves had an impact on equation (3). Using the simulation script in Figure #4 of my [GRF Equation](#), you should be able to modify the code to do the same things I have done here.

I will restate the point: you can verify everything put forward here. You have my version of the WL8 program. You have the core of the trading script used to make the simulations. And you can improve on that script as you wish.

The changes presented are not the only ones you could apply to this strategy.

I only wanted to show some possibilities, especially if 10,000 simulations of randomly generated scenarios could corroborate those changes.

The future remains unknown. To make the point, you have 11 iterations of 10,000 simulations, each with 780 trades (some 85.8 million). They all responded to equations (1) and (3).

The program found in my [GRF Equation](#) (Figure #4) was the basis for all the simulations.

I added some modifications to the code to extract the information I wanted but did not alter its central equation, which served for all the above simulations.

I only touched Type-A and Type-D trades. I could perform many other simulations based on other modifications. These include finding procedures to convert Type-D trades into no-loss Type-C trades, reducing the average loss per losing trade. This could be done by finding ways to step aside if the market conditions did not appear favorable. You might not be right most of the time, but at least you would get some and more than enough to make a difference.

Figure #12: 10,000 Simulations With 10 D to A, Type-A +10%, Type-D -10%.

# of Sims: 10,000 over 15 years using randomly selected trades based on WL8 sim metrics.						
Total: \$	89,903,166	Sim #:	1	(A: 132, B: 257, C: 219, D: 172)	CAGR:	57.37 %
W/Diff.: \$	2,971,774,997	Sim #:	1	(A: 142, B: 257, C: 219, D: 162)	CAGR:	98.70 %
Total: \$	464,424,950	Sim #:	1,000	(A: 127, B: 278, C: 226, D: 149)	CAGR:	75.57 %
W/Diff.: \$	12,783,669,320	Sim #:	1,000	(A: 137, B: 278, C: 226, D: 139)	CAGR:	119.00 %
Total: \$	1,323,215,226	Sim #:	2,000	(A: 133, B: 287, C: 216, D: 144)	CAGR:	88.27 %
W/Diff.: \$	36,925,399,340	Sim #:	2,000	(A: 143, B: 287, C: 216, D: 134)	CAGR:	135.05 %
Total: \$	411,460,262	Sim #:	3,000	(A: 141, B: 245, C: 241, D: 153)	CAGR:	74.16 %
W/Diff.: \$	12,910,639,109	Sim #:	3,000	(A: 151, B: 245, C: 241, D: 143)	CAGR:	119.14 %
Total: \$	82,539,345	Sim #:	4,000	(A: 125, B: 252, C: 241, D: 162)	CAGR:	56.47 %
W/Diff.: \$	2,429,472,508	Sim #:	4,000	(A: 135, B: 252, C: 241, D: 152)	CAGR:	96.05 %
Total: \$	515,687,916	Sim #:	5,000	(A: 134, B: 265, C: 231, D: 150)	CAGR:	76.80 %
W/Diff.: \$	15,059,935,584	Sim #:	5,000	(A: 144, B: 265, C: 231, D: 140)	CAGR:	121.41 %
Total: \$	907,068,637	Sim #:	6,000	(A: 152, B: 259, C: 208, D: 161)	CAGR:	83.59 %
W/Diff.: \$	32,529,554,922	Sim #:	6,000	(A: 162, B: 259, C: 208, D: 151)	CAGR:	133.07 %
Total: \$	65,594,276	Sim #:	7,000	(A: 128, B: 257, C: 223, D: 172)	CAGR:	54.10 %
W/Diff.: \$	2,103,735,878	Sim #:	7,000	(A: 138, B: 257, C: 223, D: 162)	CAGR:	94.18 %
Total: \$	197,264,325	Sim #:	8,000	(A: 121, B: 263, C: 248, D: 148)	CAGR:	65.83 %
W/Diff.: \$	5,156,693,024	Sim #:	8,000	(A: 131, B: 263, C: 248, D: 138)	CAGR:	106.14 %
Total: \$	297,344,893	Sim #:	9,000	(A: 125, B: 289, C: 207, D: 159)	CAGR:	70.43 %
W/Diff.: \$	8,587,765,708	Sim #:	9,000	(A: 135, B: 289, C: 207, D: 149)	CAGR:	113.27 %
Total: \$	1,264,408,482	Sim #:	10,000	(A: 141, B: 287, C: 197, D: 155)	CAGR:	87.70 %
W/Diff.: \$	40,178,595,734	Sim #:	10,000	(A: 151, B: 287, C: 197, D: 145)	CAGR:	136.37 %
Average : \$ 862,286,020 CAGR: 82.97 %						
Average + 10 diff.: \$ 26,039,996,913 CAGR: 129.64 %						
Average increase : 3,019.88 % An expected increase of: \$25,177,710,893						

[\(Click here to enlarge\)](#)

You have the trading script in Figure #4 of [GRF Equation](#) to experiment with. Changing or adding trading rules can change the number of trades and their distributed outcomes in the four trade types.

The number within each group can vary just as the average percent win or loss per winning or losing trade. The outcomes will respect the structure of equations (1) and (3). Your program changes will impact the result of the trading script, even with slight trade-type modifications. Your primary interest should be determining the long-term impact your modifications might have over many years.

You will not escape some of those drawdowns; they are part of the nature of the stock market. And even more so when trading a 3x-leveraged ETF such as TQQQ.

Even Figure #18 in my *GRF Equation*, more than suggests that the 10,000 simulations over the first year had a negative expected return, small albeit but still negative. However, as the years increase, so does the expected and achievable CAGR. That is the most critical point to make. Your future path will not be as smooth as that curve. Nonetheless, your average should be relatively close to those results.

We could consider the above simulations as if starting on day one as an extension of the WL8 simulation metrics. As such, each simulation can represent a 15-year estimate of its future outcome based on the random selection of trades. Doing 10,000 simulations enabled the use of long-term averages on these portfolio metrics.

I see many ways of improving this trading strategy. Some would require minor program modifications to move trade types from one type to another. Others could be more concentrated on increasing the average percent win per winning trade while reducing the average loss per losing trade. At the same time, other procedures could increase Trade-A and Trade-B types. It is all in your hands.

The market does not stand still. And whatever you do, you will have to sail this tumultuous and unpredictable sea of variance. Validate all you intend to do and ride the waves. There are many coming. You might have a rough sea, but your boat will not sink.

Related Papers and Articles:

[The One Percent Per Week TQQQ Trading Strategy: MY EQUATION](#)

[One Percent Per Week Strategy: Some Trading Habits](#)

[One Percent Per Week Strategy: Trade Distribution](#)

[THE TQQQ 3x-LEVERAGED SCENARIO](#)

[For Your Retirement, You Need To Win. It Is Not A Wish](#)

[You Can Make It Big, Real Big. If You Want](#) *With Excel template.*

[Make Your First \\$50M Before You Retire](#)

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[High Stock Portfolio Returns? Easy](#)

[Stock Trading Strategy Alpha Generation](#)

[There Is Always A Better Retirement Fund: \[Part I\]\(#\), and \[Part II\]\(#\)](#)

[The One Percent a Week Stock Trading Program: \[Part VII\]\(#\), and \[Part VIII\]\(#\)](#)

[The One Percent a Week Stock Trading Program: \[Part V\]\(#\), and \[Part VI\]\(#\)](#)

[The One Percent a Week Stock Trading Program: \[Part III\]\(#\), and \[Part IV\]\(#\)](#)

[The One Percent a Week Stock Trading Program: \[Part I\]\(#\), and \[Part II\]\(#\)](#)

[The Long-Term Stock Trading Problem: \[Part I\]\(#\), and \[Part II\]\(#\)](#)

[QQQ To The Rescue](#)

[Take the Money and Keep it – II](#)

[Use QQQ - Make the Money and Keep IT](#)